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Estimation and Compensation of Clipping Noise in OFDMA Systems

Ying Chen, Jian (Andrew) Zhang, A. D. S. Jayalath

***Abstract*—We propose an efficient and low-complexity scheme for estimating and compensating clipping noise in OFDMA systems. Conventional clipping noise estimation schemes, which need all demodulated data symbols, may become infeasible in OFDMA systems where a specific user may only know his own modulation scheme. The proposed scheme first uses equalized output to identify a limited number of candidate clips, and then exploits the information on known subcarriers to reconstruct clipped signal. Simulation results show that the proposed scheme can significantly improve the system performance.**

I. Introduction

High peak-to-average power ratio (PAPR) is a well-known problem in orthogonal frequency-division multiplexing (OFDM) systems. As the multi-user version of OFDM, orthogonal frequency-division multiple access (OFDMA) has severer PAPR problem because of significantly increased number of subcarriers. Numerous solutions [1] have been investigated for the problem in OFDM systems. As one simple solution, clipping, and in particular, soft clipping reduces the magnitude of large signals to a predefined threshold while leaving their phase unchanged. Clipping noise introduced by the magnitude distortion degrades the system performance. Some approaches have been investigated to mitigate the noise, including decision aided reconstruction [2], iterative clipping noise estimation [3], and over-sampling based clipping noise reconstruction [4].

Estimation and compensation for clipping noise in the downlink of OFDMA systems faces special challenges as *each user only has limited knowledge of the whole signal*. Since there are flexible modulation schemes for different users, it is not always possible for a particular user to know the modulation schemes of all other users. Most of the clipping noise estimation schemes proposed for OFDM systems are based on the decision directed approach which requires demodulated data symbols. Lack of modulation knowledge at some of the subcarriers prevents these schemes from being applied in OFDMA systems. To the authors' best knowledge, the iterative reconstruction-based method presented in [5] is the only feasible one in this scenario.

Different to [5] where *signal* is recovered iteratively, in this letter, we propose a novel *clipping-noise recovery* scheme for OFDMA systems which does not depend on decision-directed approach and exploits "known subcarriers" instead. Here, we use the term known subcarriers for all tones with either known symbols or zeros, which may include pilots and guarding-band tones. There are generally quite a few known subcarriers in practical OFDMA systems. For example, in WiMAX, 10% of subcarriers are known to a receiver. After clipping, they contain measurable power mapped from clipping noise. However, estimating clipping noise directly/solely with known subcarriers is infeasible as there are less known samples than variables (clips) to be determined when the position of clips is unknown. The proposed scheme first locates some potential clipped samples by using equalized signals, and then solves determined equations to refine and determine clipping noise by using information at known subcarriers.

II. System Model

In a K-user OFDMA system with M subcarriers, let $\mathcal{V}_k$ denote the set of subcarriers assigned to user k and $X_k(m), m \in \mathcal{V}_k$ be user-k's data symbols, and let $\mathcal{R}$ denote the index set of the L_r known subcarriers. The time domain baseband signal can be represented by

$$\begin{aligned} x(n) =& \frac{1}{\sqrt{M}} \sum_{k=1}^{K} \sum_{m \in \mathcal{V}_k} X_k(m) e^{j2\pi nm/M} + \\ & \frac{1}{\sqrt{M}} \sum_{r \in \mathcal{R}} X(r) e^{j2\pi nr/M},\ n \in [0, M-1]. \end{aligned} \tag{1}$$

It is well-known that when M is large, the magnitude of $x(n)$ is Rayleigh distributed and the signal has a large dynamic range, which causes the PAPR problem. When a soft clipper with a pre-defined clipping threshold A_s is used, the output signal after clipping becomes

$$x_c(n) = \begin{cases} x(n) & |x(n)| < A_s \\ \frac{x(n)}{|x(n)|} A_s & |x(n)| \geq A_s \end{cases}. \tag{2}$$

For clipped samples, the clipping noise is given by $e_c(n) = x_c(n) - x(n)$.

For user k, the received frequency-domain signal at the m^{th} subcarrier is given by

$$Y(m) = H(m) X_c(m) + W(m), \tag{3}$$

where $\{X_c(m)\}$ is the Fourier transform of $\{x_c(n)\}$, $H(m)$ is the frequency-domain channel response, and $W(m)$ denotes the Gaussian noise in the frequency domain. After a zero-forcing channel equalization, the output is

$$Z(m) = Y(m)/H(m) = X_c(m) + W(m)/H(m). \tag{4}$$

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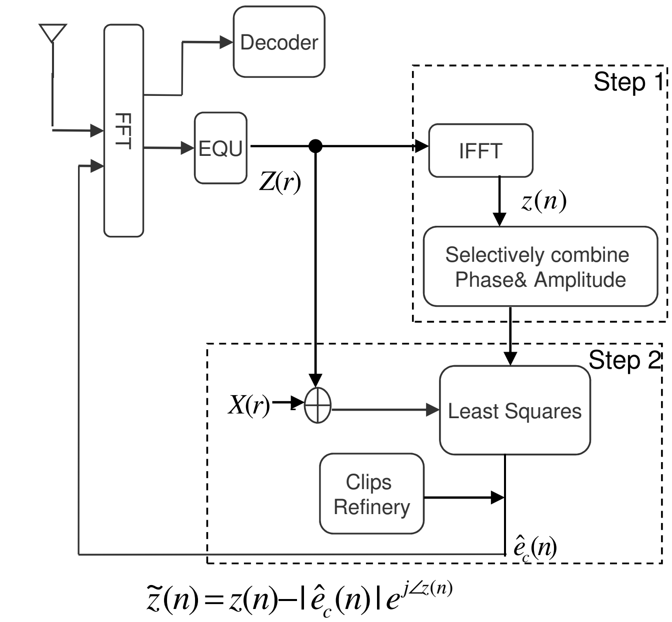

Fig. 1. Block diagram of the proposed scheme

A demodulation process is then applied to find the estimate of $X(m)$:

$$\hat{X}(m) = \arg\min_{\chi} |Z(m) - \chi|^2, \ m \in \mathcal{V}_k, \tag{5}$$

where χ denotes the constellation points of user k's modulation.

III. Estimation of Clipping Noise

The block diagram of the proposed scheme is shown in Fig. 1. It consists of two steps: 1) based on all equalized samples $Z(m)$, locate a set of candidates of clips and determine their phase; and 2) refine the set and determine their magnitude by forming and solving determined equations with information at known subcarriers.

A. Candidate Clips Localization and Phase Estimation

In the literature, two signal sources are typically exploited to locate potential clips: the demodulated signal from (5) [3] and the difference between the equalized output $Z(m)$ and the demodulated output $\hat{X}(m)$ [6]. However, in an OFDMA system, different users could use different modulations, and each user generally only knows his own modulation scheme. Thus these two signal sources can not be used. Next, we show an alternative source which does not depend on modulation schemes.

Applying an inverse Fast Fourier transform (IFFT) to all the equalized samples $Z(m), m = 0, \cdots, M-1$, we obtain

$$z(n) = x_c(n) + \xi(n), \, n \in [0, M-1], \tag{6}$$

where $\{\xi(n)\}$ are the inverse Fourier transform of $\{W(m)/H(m)\}, m \in [0, M-1]$.

Although small $H(m)$ could cause severe noise enhancement in the frequency domain, the probability of $\xi(n)$ having large values is relatively small thanks to the averaging effect of the IFFT. For reliable communications, the averaged per-bit signal-to-noise-power ratio of the received signal is generally larger than 15dB. Thus we have

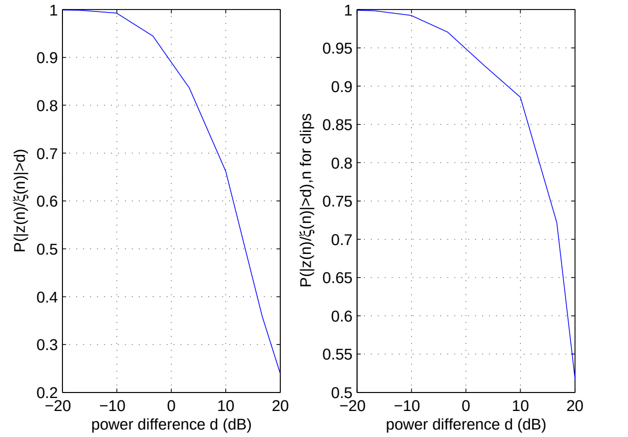

Fig. 2. ICDF of the power ratio between $z(n)$ and $\xi(n)$ for all n (left sub-figure) and for n corresponding to clips only (right sub-figure). The system configuration is detailed in Section V.

$$|z(n)| \gg |\xi(n)|, \tag{7}$$

which is particularly true for clipped samples. This is evident from Fig. 2, where the inverse cumulative density function (ICDF) for the power ratio between $z(n)$ and $\xi(n)$ is plotted. This property is exploited to locate the candidate clips and estimate their phase.

There may be some variations for locating candidate clips by exploring (7). The basic idea is to find and pick up those samples with magnitude close to A_s. This works with or without the knowledge of A_s. When A_s is unknown, candidate clips can be picked up from the largest samples; when A_s is known, a threshold slightly smaller than A_s can be used. Here, we assume A_s is known and suggest to use the threshold $A_s - \mu\sigma_w$ where σ_w is the standard deviation of the noise and μ is a scalar. With $\mu = 2$ used, it means 86% of noise samples are smaller than $2\sigma_w$, so the magnitude of most of the clipped samples is larger than this threshold. In this way, any $z(n)$ with magnitude larger than $A_s - \mu\sigma_w$ will be picked up as candidate clips.

Since the soft clipper does not change the phase of the clipped signal and $|z(n)| \gg |\xi(n)|$, we can easily obtain the phase of the candidate clips

$$\angle(e_c(n)) = \angle(x_c(n)) \simeq \angle(z(n)), \text{ for } n \in \mathcal{C}. \tag{8}$$

where $\mathcal{C}$ denotes the index set of the candidate clips. The set of clipped samples is denoted by $\mathbf{e}_c = \{e_c(p)\}, p \in \mathcal{C}$, and the length of the set is L_c.

B. Clips Refinery and Magnitude Estimation

After locating the candidate clips, a limited number of samples which are possibly clipped are picked up. If these candidate clips are more than the known subcarriers, we can reduce the size of the candidate set by increasing μ and relocating candidate clips. Alternatively, we can choose not to do compensation for this OFDMA symbol. When $L_c \leq L_r$, a refining process using known subcarriers can then be applied to find out the true clips and their magnitude.

First, compute the difference between $Z(r)$ and $X(r)$ for known subcarriers

$$\delta(r) \triangleq Z(r) - X(r),\ r \in \mathcal{R}, \tag{9}$$

where $X(r)$ is known in advance. The difference is caused by equalized AWGN sample and the clipping noise. Considering all the known subcarriers, we have

$$\boldsymbol{\delta} = \mathbf{F}_{r,c}\mathbf{e}_c + \boldsymbol{\eta}, \tag{10}$$

where $\boldsymbol{\delta} = \{\delta(r)\}, r \in \mathcal{R}$, $\boldsymbol{\eta}$ is the noise vector containing $\{W(r)/H(r)\}, r \in \mathcal{R}$ and possibly some residual clipping noise which is missed in $\mathcal{C}$, and $\mathbf{F}_{r,c}$ is a $L_r \times L_c$ sub-matrix of the FFT matrix $\mathbf{F}$, containing its $r, r \in \mathcal{R}$ rows and $c, c \in \mathcal{C}$ columns. When $L_r \geq L_c$, $\mathbf{F}_{r,c}$ is a tall or square matrix, and generally has rank equal to the number of columns. Thus $\mathbf{e_c}$ can be solved by using, e.g., a least squares (LS) method

$$\hat{\mathbf{e}}_c = (\mathbf{F}_{r,c}^H\mathbf{F}_{r,c})^{-1}\mathbf{F}_{r,c}^H\boldsymbol{\delta}, \tag{11}$$

where the superscript ^{H} and $^{-1}$ denote the matrix conjugate transpose and inversion, respectively.

Since the candidate clips picked up earlier contain some samples which are not actually clipped, a threshold, e.g., the noise variance, can be applied to $|\hat{\mathbf{e}}_c|$ to remove those smaller estimates and refine the set. This also means only larger clips will be compensated.

Because the phase estimates obtained from (8) are more accurate, only the magnitude obtained from (11) is adopted in reconstructing clipping noise.

A user can also add his data tones to the known subcarrier set for clip estimation in a decision directed approach. Similar to (9), for the data tones of user k, we can define the difference

$$\delta_k(m) \triangleq Z(m) - \hat{X}(m),\ m \in \mathcal{V}_k. \tag{12}$$

Note that $\delta_k(m)$ not only includes equalized AWGN sample and clipping noise, but also possible mapping error. Thus it is preferable to use these data subcarriers when the SNR is high.

C. Summary of the Estimation and Compensation Scheme

A summary of the proposed estimation and compensation scheme is as follows:

1) Equalize the frequency-domain received signal and get $Z(m), m \in [0, M-1]$, and generate its time-domain samples $z(n), n \in [0, M-1]$;
2) Determine candidate clips by picking up those with magnitude larger than a predefined threshold from $z(n), n \in [0, M-1]$;
3) Find $\delta(r) = Z(r) - X(r),\ r \in \mathcal{R}$, and compute $\hat{\mathbf{e}}_c = (\mathbf{F}_{r,c}^H\mathbf{F}_{r,c})^{-1}\mathbf{F}_{r,c}^H\boldsymbol{\delta}$;
4) Refine the set of clips by removing those with $|\hat{e}_c(n)|$ smaller than another threshold from the set $\mathcal{C}$, and get an updated set of clips $\tilde{\mathcal{C}}$;
5) Compensate signals in the time domain by $\tilde{z}(n) = z(n) - |\hat{e}_c(n)| \exp(j\angle(z(n))), n \in \tilde{\mathcal{C}}$. Convert $\tilde{z}(n)$ to the frequency domain for demodulation.

IV. Low Complexity Algorithms for Amplitude Estimation

The LS method in (11) requires to compute a matrix inverse, which could lead to two problems: 1) The complexity of the pseudo-inverse in (11) is high when the number of candidate clips is large; and 2) Large estimation errors could be generated when $\mathbf{F}_{r,c}$ is near singular. In this section, we propose a low-complexity iterative scheme for magnitude estimation.

A. Iterative Scheme

The proposed iterative scheme follows the principle of band-limited signal recovery in [7] which tries to recover the whole band-limited time-domain signal from a segment of its frequency-domain signal. Our proposed algorithm is based on interpreting (10) as the band-limited signal recovery problem when ignoring the noise term. To present the algorithm in a way closer to that in [7], we extend the sub-matrix $\mathbf{F}_{r,c}$ to the square full matrix $\mathbf{F}$ in (10), and vectors are padded with zeros accordingly. With $\boldsymbol{\delta}$, L_r out of M frequency-domain samples, we want to estimate an $M \times 1$ time-domain vector, which only has L_c non-zero values $\mathbf{e}_c$ at known locations.

Denote the estimate of the $M \times 1$ time-domain vector as $\mathbf{e}_i$, and its frequency-domain dual as $\boldsymbol{\delta}_i$, where i stands for the i^{th} iteration. We can represent $\mathbf{e}_i$ as

$$\mathbf{e}_i = \mathbf{I}_c\mathbf{F}^H\boldsymbol{\delta}_i, \tag{13}$$

where $\mathbf{I}_c$ is an $M \times M$ diagonal matrix with diagonal elements of index $(n, n), n \in \mathcal{C}$ being 1 and others being 0. Following the signal recovery process in [7], we have

$$\boldsymbol{\delta}_i = \mathbf{I}_r\mathbf{F}\mathbf{e}_{i-1} + \boldsymbol{\delta}_0, \tag{14}$$

where $\mathbf{I}_r$ is an $M \times M$ diagonal matrix with diagonal elements of index $(n, n), n \in \mathcal{R}$ being 0 and others being 1, and $\boldsymbol{\delta}_0$ is an $M \times 1$ vector with elements of index $r, r \in \mathcal{R}$ being $\delta(r)$ and others zeros. In the iterations, samples at known subcarriers remain unchanged, while other samples are updated.

The initial estimate of the clipping error (denoted by $\mathbf{e}_0$) is obtained from

$$\mathbf{e}_0 = \mathbf{I}_c\mathbf{F}^H\boldsymbol{\delta}_0, \tag{15}$$

and $\mathbf{e}_i, i \geq 1$ is updated by

$$\mathbf{e}_i = \mathbf{I}_c\mathbf{F}^H\mathbf{I}_r\mathbf{F}\mathbf{e}_{i-1} + \mathbf{I}_c\mathbf{F}^H\boldsymbol{\delta}_0 = \mathbf{I}_c\mathbf{F}^H\mathbf{I}_r\mathbf{F}\mathbf{e}_{i-1} + \mathbf{e}_0. \tag{16}$$

1) Convergency and Iteration Stop Condition: We can examine the convergence property under the mean-squared-error (MSE) criterion. Let $\mathbf{e} = \{e_c(0), e_c(1), \cdots, e_c(M-1)\}$ be the $M \times 1$ vector containing the true clips, where $e_c(n) = 0$ for non-clipped samples, and $\boldsymbol{\delta}_c = \{\delta_c(0), \delta_c(1), \cdots, \delta_c(M-1)\}$ be its corresponding frequency-domain samples. The MSE of the estimate $\mathbf{e}_i$ and $\boldsymbol{\delta}_i$ can be computed as $\varepsilon_{e_i}^2 =$

$\frac{1}{M}\sum_{n=0}^{M-1}|e_i(n)-e_c(n)|^2$, and $\varepsilon^2_{\delta_i}=\frac{1}{M}\sum_{n=0}^{M-1}|\delta_i(n)-\delta_c(n)|^2$ respectively.

Let $\mathbf{e}_i^s \triangleq \mathbf{F}^H\boldsymbol{\delta}_i$, and we have $\mathbf{e}_i^s-\mathbf{e}_c=\mathbf{F}^H(\boldsymbol{\delta}_i-\boldsymbol{\delta}_c)$. Parseval's theorem shows that $\varepsilon^2_{e_i^s}=\varepsilon^2_{\delta_i}$, where $\varepsilon^2_{e_i^s}$ and $\varepsilon^2_{\delta_i}$ represent the MSE of $\mathbf{e}_i^s$ and $\boldsymbol{\delta}_i$ respectively. In addition, since $\mathbf{e}_i$ is constructed from $\mathbf{e}_i^s$ by picking up $e_i^s(n)$ $(n\in\mathcal{C})$ and putting zeros on the other samples, we have

$$\varepsilon^2_{e_i}\le\varepsilon^2_{e_i^s}=\varepsilon^2_{\delta_i},\tag{17}$$

where we assume that $\mathcal{C}$ includes all non-zero elements in $\mathbf{e}_c$.

Let $\boldsymbol{\delta}_i^s\triangleq\mathbf{F}\mathbf{e}_{i-1}$. By applying Parseval's theorem, we have $\varepsilon^2_{\delta_i^s}=\varepsilon^2_{e_{i-1}}$, where $\varepsilon^2_{\delta_i^s}$ denotes the MSE of $\boldsymbol{\delta}_i^s$. As shown in (14), $\boldsymbol{\delta}_i$ is constructed by substituting $\delta_c(n)$ for the n-th $(n\in\mathcal{R})$ elements of $\boldsymbol{\delta}_i^s$. So we have

$$\varepsilon^2_{\delta_i}\le\varepsilon^2_{\delta_i^s}=\varepsilon^2_{e_{i-1}}.\tag{18}$$

Introducing (18) to (17), we obtain $\varepsilon^2_{e_i}\le\varepsilon^2_{e_{i-1}}$, which reveals that the MSE will not increase with increasing iteration order and converges. Hence the condition of stopping iteration is $\varepsilon^2_{e_i}=\varepsilon^2_{e_{i-1}}$, which implies $\varepsilon^2_{e_i}=\varepsilon^2_{\delta_i}$.

The iteration-stopping condition shows that if there are still errors in $\mathbf{e}_i$, these errors are not located at the known subcarriers. In other words, there is no error at the known subcarriers, which yields $\mathbf{I}_r\boldsymbol{\delta}_c=\mathbf{I}_r\mathbf{F}\mathbf{e}_i$. Removing zeros in symbols and writing it in a compact form, we get $\boldsymbol{\delta}=\mathbf{F}_{r,c}\mathbf{e}_c$, which matches the noise-free result of (10). Thus the iterative method converges to the LS solution.

The iterative method only uses matrix multiplication, thus in the presence of noise, it may outperform the LS method via avoiding the noise enhancement and stability problems which the LS method may encounter in the process of computing matrix pseudo-inversion.

B. Pre-stored Matrix Solution

Several size-M FFTs and IFFTs are required to compute (16) in the iterative scheme. Although its complexity is lower than the pseudo-inverse scheme, it is still high when M is large. Since $\mathbf{I}_r$ is known in (16), we can reduce the complexity in the iterative method by pre-calculating and saving $\mathbf{G}=\mathbf{F}^H\mathbf{I}_r\mathbf{F}$. Thus (16) can be rewritten as

$$\mathbf{e}_i=\mathbf{I}_c\mathbf{G}\mathbf{e}_{i-1}+\mathbf{e}_0=\mathbf{I}_c\mathbf{G}\mathbf{I}_c\mathbf{e}_{i-1}+\mathbf{e}_0,\tag{19}$$

where in the second equality, we have used $\mathbf{e}_{i-1}=\mathbf{I}_c\mathbf{e}_{i-1}$.

In (19), only those elements with index n, $n\in\mathcal{C}$, have non-zero values in all the addends. So we can compute $\mathbf{G}_c\triangleq\mathbf{I}_c\mathbf{G}\mathbf{I}_c$ and store it for the iteration, and the iteration equation becomes

$$\mathbf{e}_i=\mathbf{G}_c\mathbf{e}_{i-1}+\mathbf{e}_0.\tag{20}$$

Since $\mathbf{G}_c$ only has $L_c\times L_c$ non-zero elements, (20) can be rewritten in a compact form, and its complexity is low when L_c is small.

C. Complexity Comparison

Here, the complexity is evaluated with the number of multiplications. The complexity of computing the pseudo-inverse of $\mathbf{F}_{r,c}$ in (10) is in the order of $\mathcal{O}(L^3), L=\max(L_c,L_r)$. The total complexity of the LS method is thus $\mathcal{O}(L^3)+L_r^2$. For the iterative algorithm, assume Q iterations are required. In the FFT/IFFT based solution, from (16), the complexity is $QM\log_2 M$ based on radix-2 FFT algorithm. In the pre-stored matrix approach, from (20), the complexity is QL_c^2 without considering the complexity associated with pre-computation.

By comparing $L_c^2(\le L_r^2)$ with $M\log_2 M$, we can see that when $L_r\le\sqrt{M\log_2 M}$, the pre-stored approach will have lower complexity than directly implementing FFT/IFFT. Since Q is generally small, computing the pseduo-inverse directly has the highest complexity in most cases.

For the approach proposed in [5], the complexity is $Q(K+1)M\log_2((K+1)M)$ where K is the ratio between the number of padded zeros and M.

V. Simulation Results

The simulated OFDMA system is configured basically following the IEEE802.16 2004 WiMAX standard [8], and 240 pilot out of total 2048 subcarriers are used for clipping noise compensation. The user of interest uses 64QAM modulation and occupies $1/8$ of the total subcarriers, in an interleaved pattern. Other data subcarriers are randomly modulated by BPSK, QPSK, 16QAM and 64QAM. The WiMAX SUI3 channel model [9] is adopted. The method in [5] is also simulated and compared. Unless noted otherwise, the clipping threshold is 4.5dB, and the number of iterations in both our iterative method and the method in [5] is 3. In the simulation, μ is fixed to 2, and no compensation is implemented when $L_r<L_c$.

We first present the BER performance for uncoded systems with various E_b/N_0 in Fig. 3. When E_b/N_0 is small, the proposed schemes show no performance improvement as candidate clips may contain notable false ones and miss true ones. It is also clear that the condition check $L_r<L_c$ avoids performance degradation in this case. At higher E_b/N_0, all compensation schemes improve BER performance, and both of our schemes outperform the method in [5]. The least squares method shows non-smooth performance because most of compensations start inappropriately at $E_b/N_0=17$dB, where compensation causes large errors although L_r is already larger than L_c. This also implies that a better condition for starting compensation in the least squares method needs to be developed.

Fig. 4 illustrates the impact of iteration times on the BER performance for the proposed iterative method. It is clear that performance improves with increasing number of iterations, and performance gap between the third and fourth iteration is insignificant, which suggests that 3 iterations are sufficient for balancing performance and complexity.

Fig. 5 shows the BER performance for uncoded systems with clipping thresholds from 4dB to 6dB, where E_b/N_0 is 24dB. For these practical clipping thresholds, the proposed schemes, and particularly the iterative one, improves system performance remarkably.

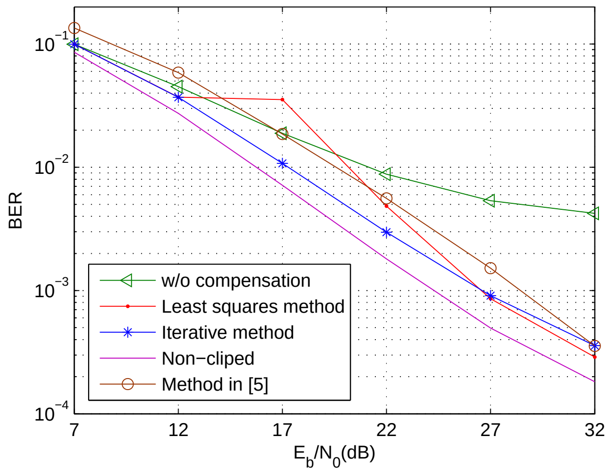

Fig. 3. BER vs E_b/N_0 for uncoded systems

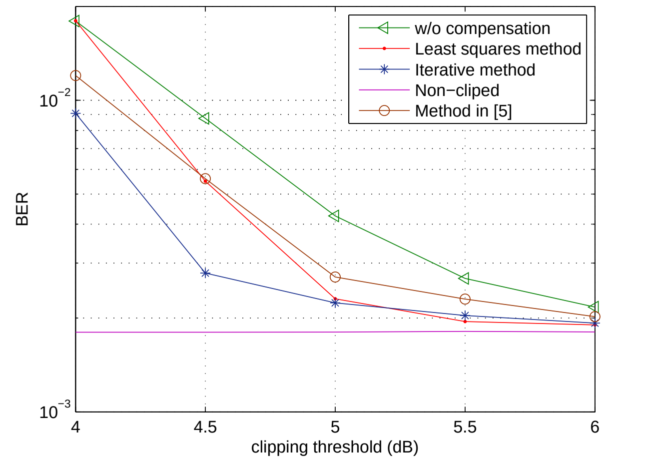

Fig. 5. BER vs clipping threshold for uncoded systems, where $E_b/N_0 =$ 22dB

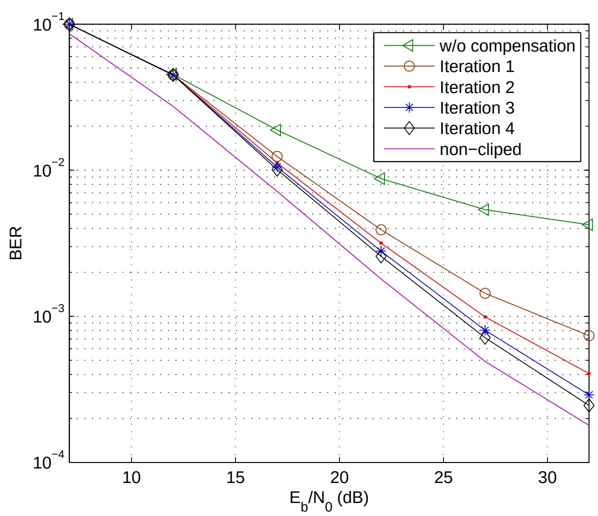

Fig. 4. Impact of iteration times on BER performance of uncoded systems

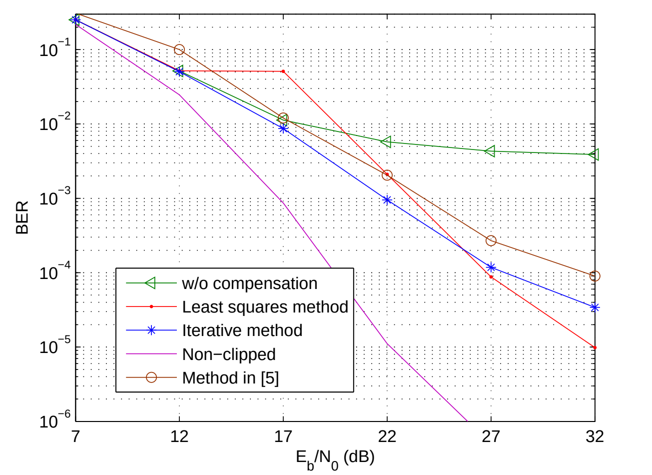

Fig. 6. BER vs E_b/N_0 for coded systems

For coded systems with $1/2$-rate convolutional code, the BER performance is presented in Fig. 6. Without compensation, we can see a BER floor at about $4 * 10^{-3}$ which cannot be reduced by coding and increasing E_b/N_0 due to the clipping noise. The proposed schemes remove this error floor and improve system performance greatly.

VI. Conclusion

We have presented an efficient and low-complexity clipping noise estimation and compensation scheme, which does not require knowledge of modulations, and is thus promising for OFDMA systems where one user generally does not know other users' modulation schemes. Simulation results show that the proposed scheme can significantly improve system performance at working SNR range.

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